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# Energy-efficient Localization Via Personal Mobility Profiling

*Ionut Constandache*

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# Context

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Pervasive wireless connectivity

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Localization technology

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Location-based applications (LBAs)

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Pervasive wireless connectivity

+

Localization technology

=

Location-based applications (LBAs)

(iPhone AppStore: 3000 LBAs, Android: 600 LBAs)

# Location-Based Applications (LBAs)

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- Two kinds of LBAs:

- One-time location information:

- Geo-tagging, location-based recommendations, etc.

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### ■ One-time location information:

Geo-tagging, location-based recommendations, etc.

### ■ Localization over long periods of time:

GeoLife: shopping list when near a grocery store

TrafficSense: real-time traffic conditions

# Localization Technology

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| <u>Accuracy</u> | <u>Technology</u> |
|-----------------|-------------------|
| 10m             | GPS               |
| 20-40m          | WiFi              |
| 200-400m        |                   |
| GSM             |                   |

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Energy Efficiency is important (localization for long time)

# Localization Technology

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Ideally  
Accurate and Energy-Efficient Localization

# Energy

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... sample every 30s

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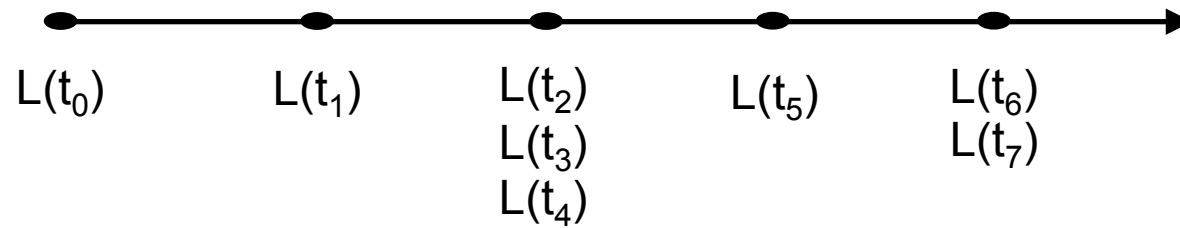
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For limited **energy** budget what **accuracy** to expect?

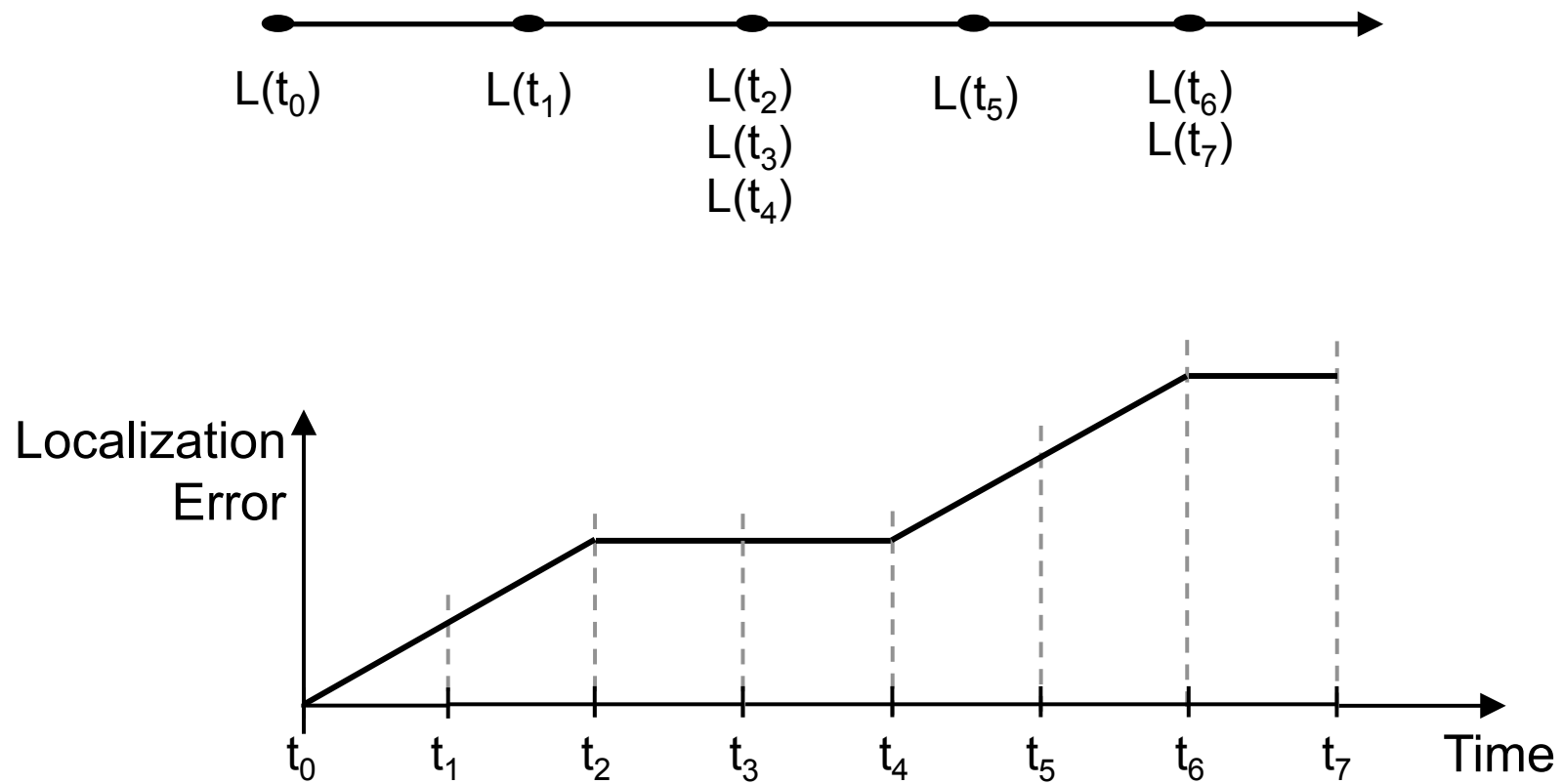
# Problem Formulation

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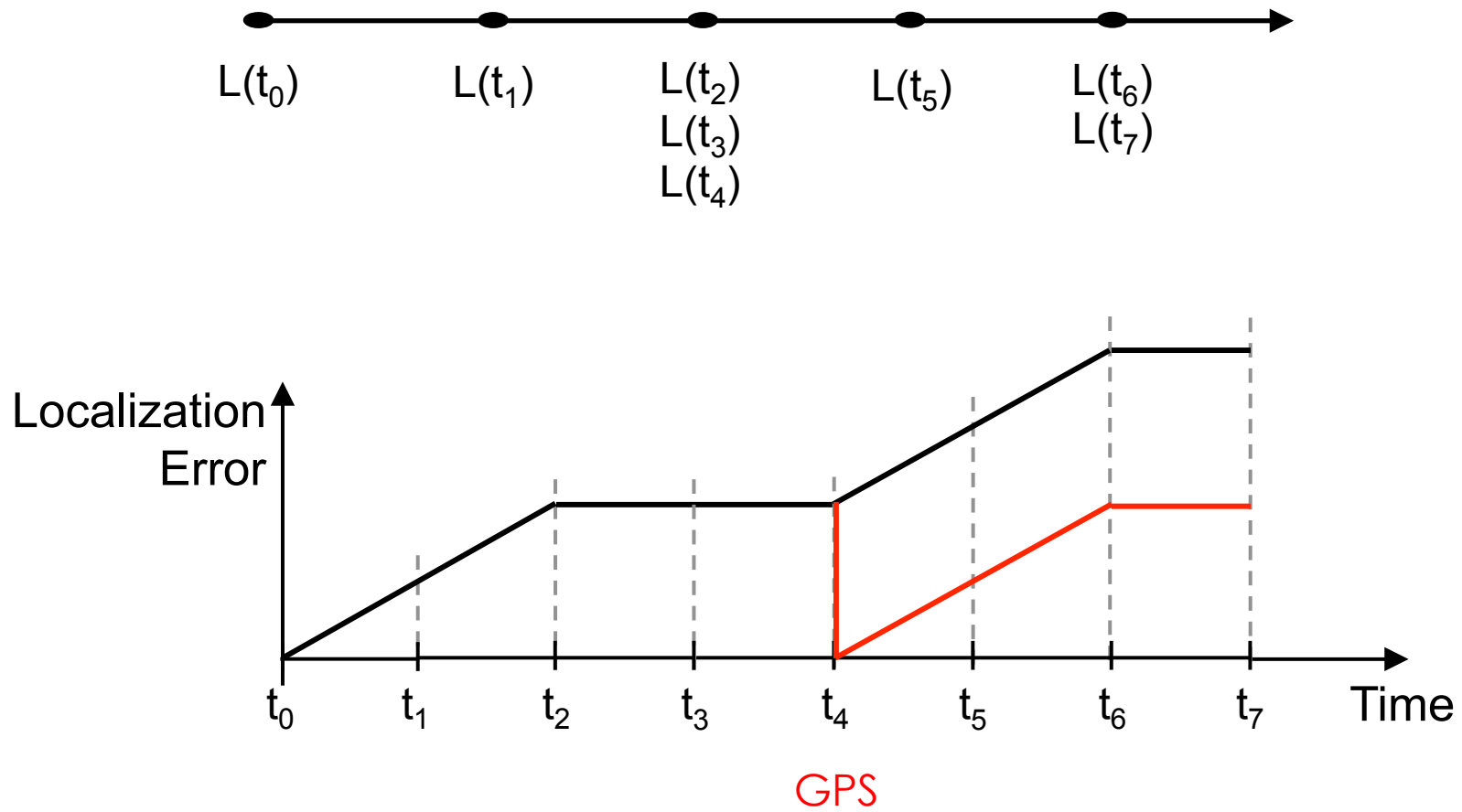
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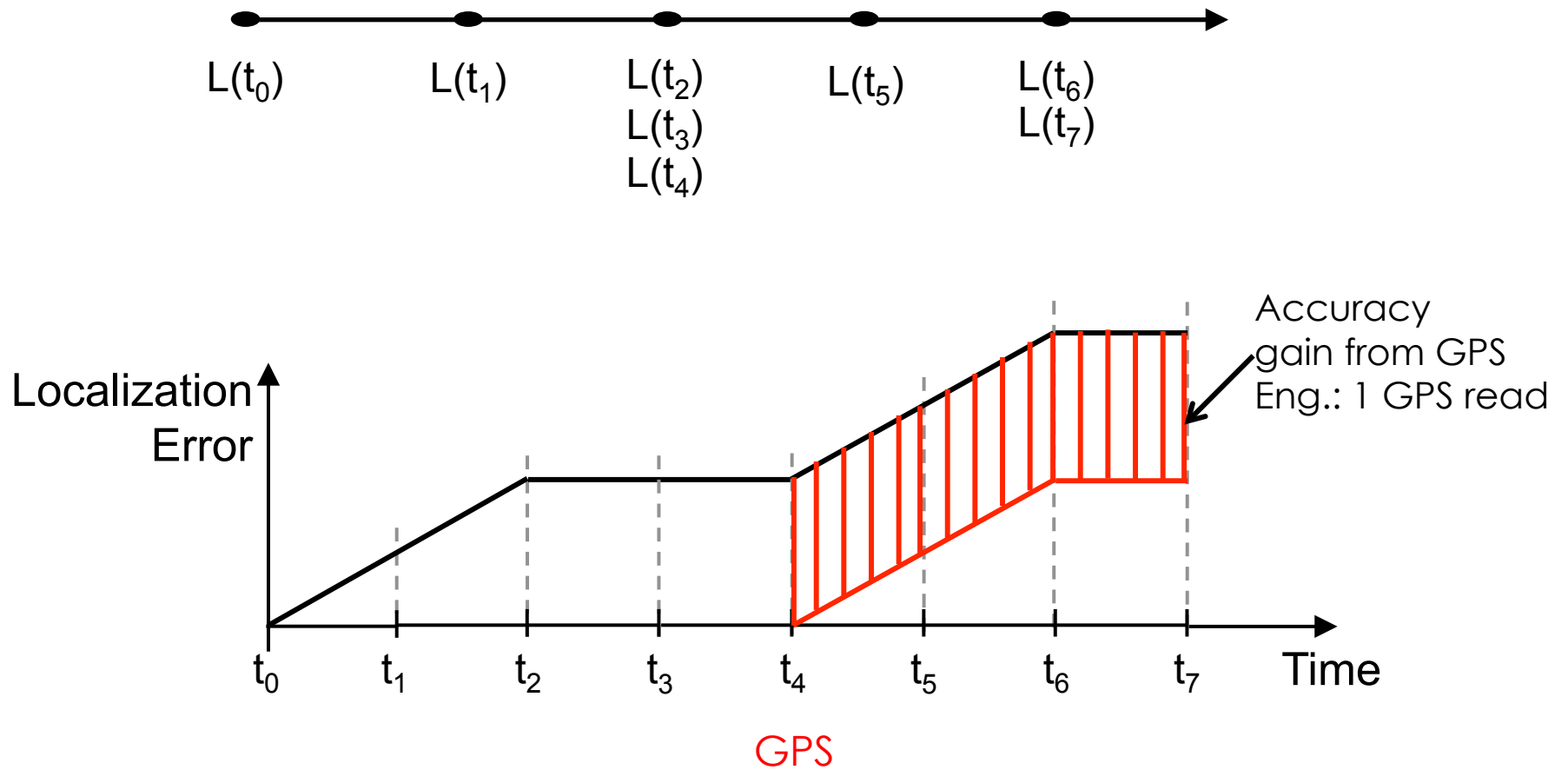
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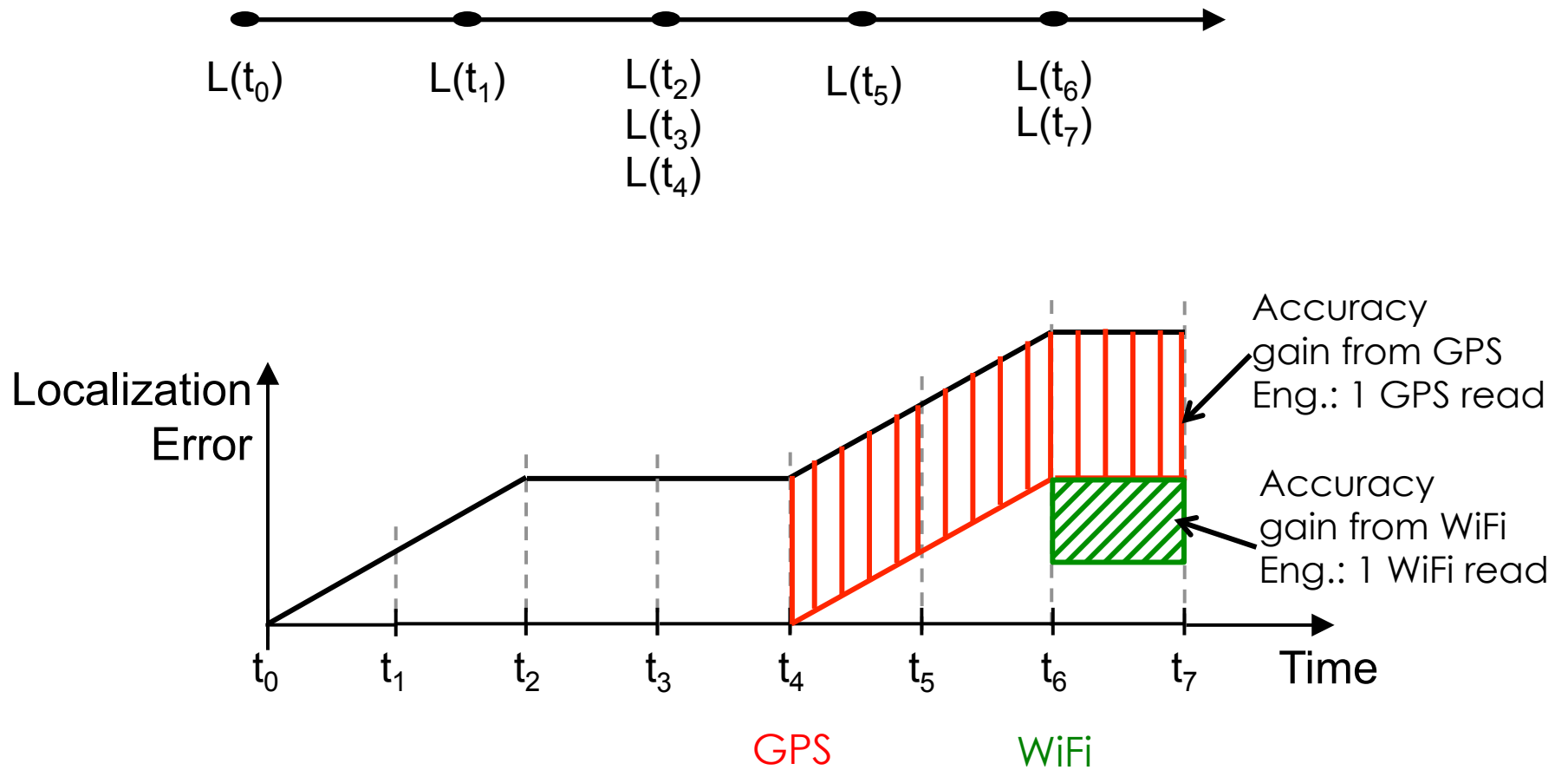


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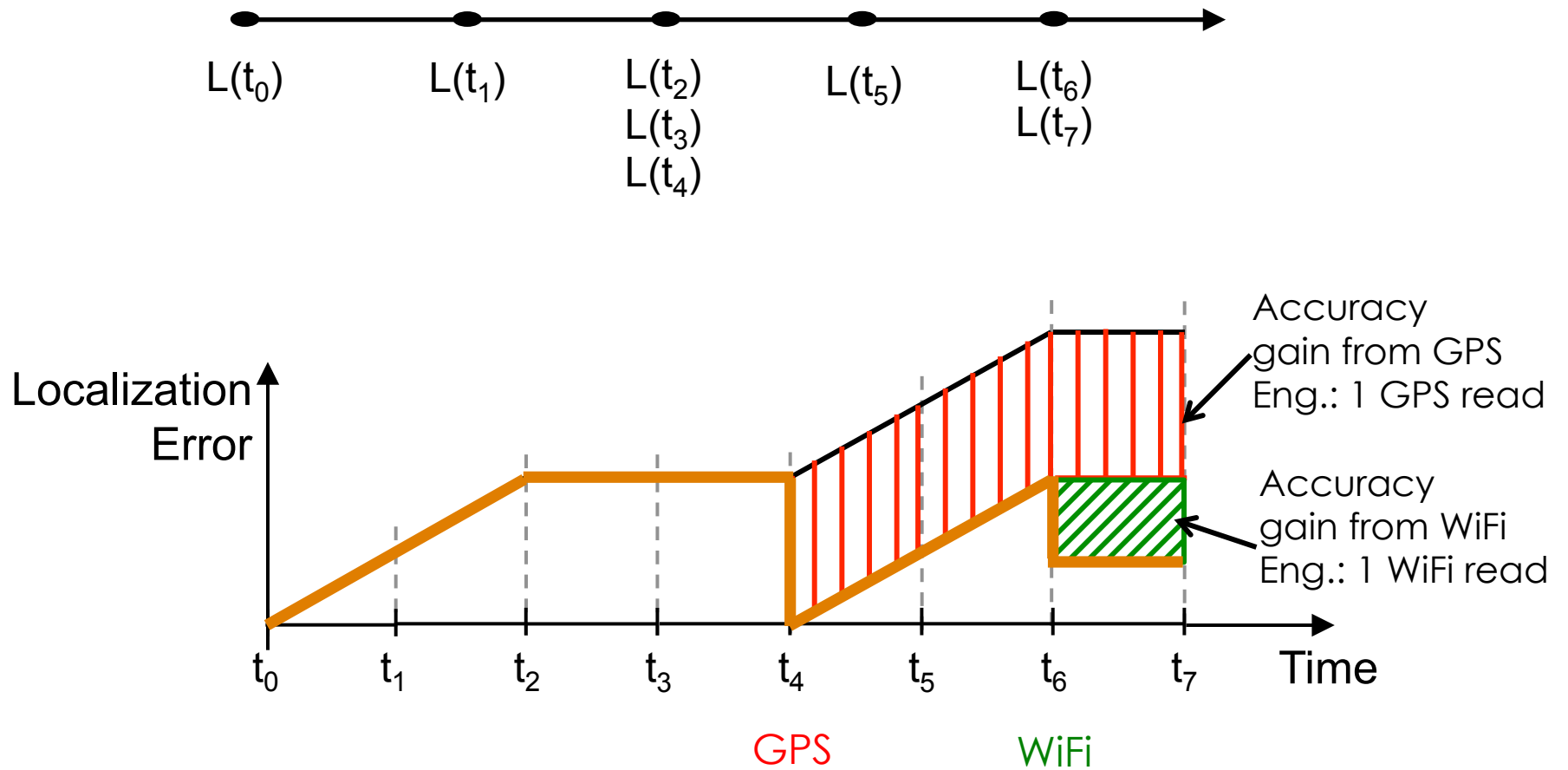
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location readings costs  $e_{\text{gps}}$ ,  $e_{\text{wifi}}$ ,  $e_{\text{gsm}}$ :

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Find the Offline Optimal Accuracy

# Results

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|         | Opt. GPS/WiFi/GSM |
|---------|-------------------|
| Trace 1 | 78.5m             |
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| Trace 3 | 62.1m             |

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Online Schemes Naturally Worse

## Our Approach: EnLoc

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  - Exploit habitual paths
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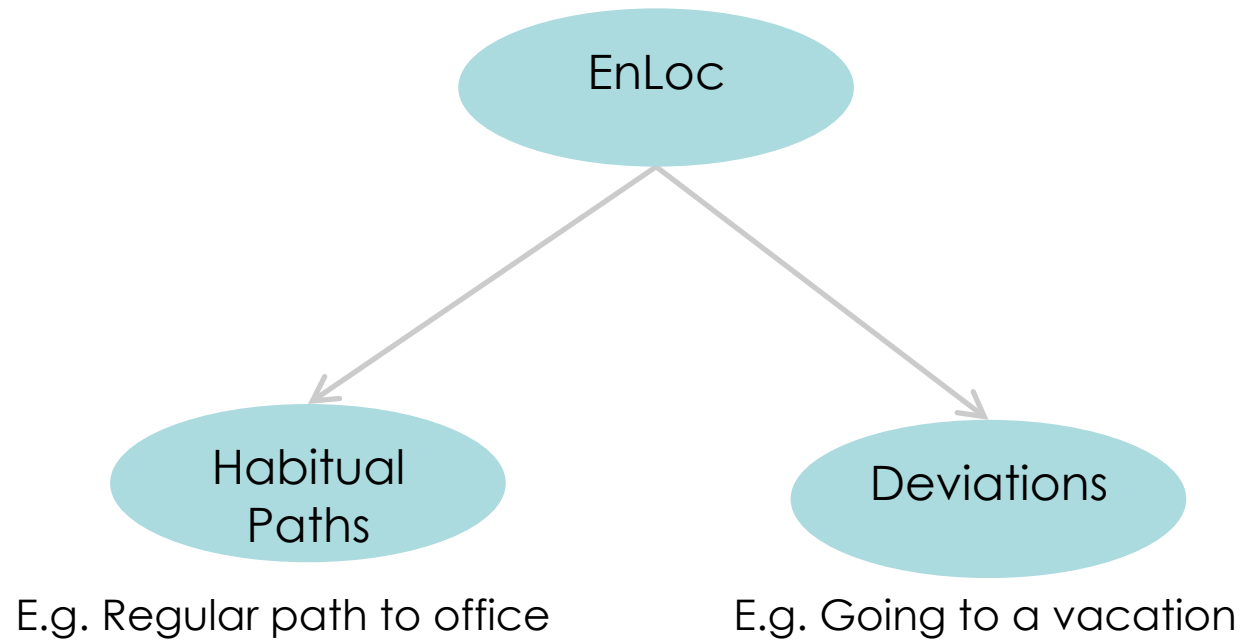
# Our Approach: EnLoc

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- Reporting last sampled location increases inaccuracy
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  - Leverage population statistics when the user has deviated
- EnLoc Solution:
  - Predict user location when not sampling
  - Sample when prediction is unreliable

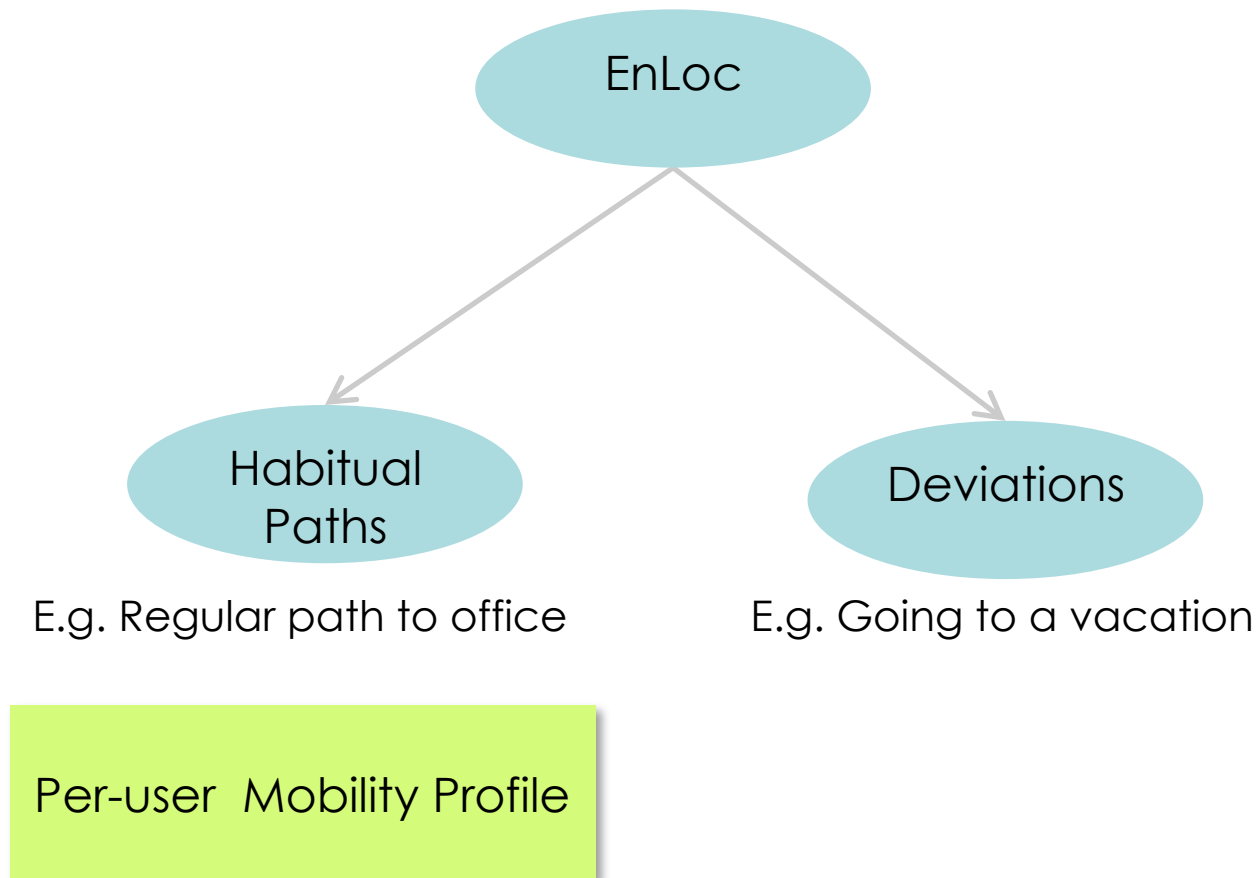
# EnLoc: Overview

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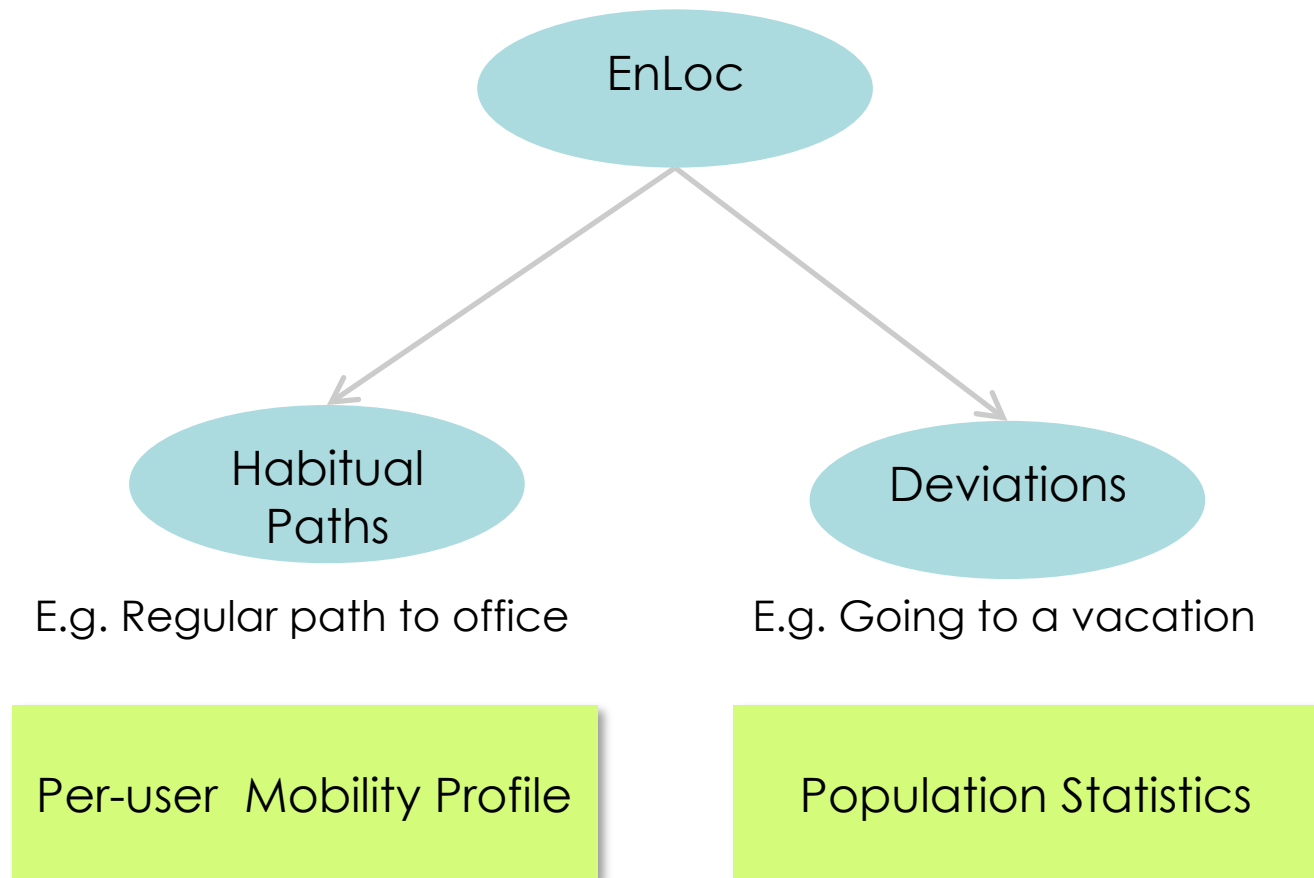
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# Profiling Habitual Mobility

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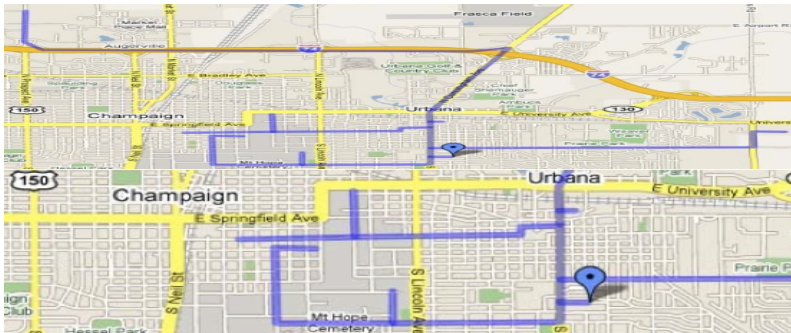
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  - Going to/from office
  - Favorite grocery shop, cafeteria
  
- Habitual activities translate into *habitual paths*
  - E.g. path from home to office
  
- Habitual paths may branch
  - E.g., left for office, right for grocery
  - Q: How to solve uncertainty?
  - A: Schedule a location reading after the branching point.

# Per-User Mobility Graph

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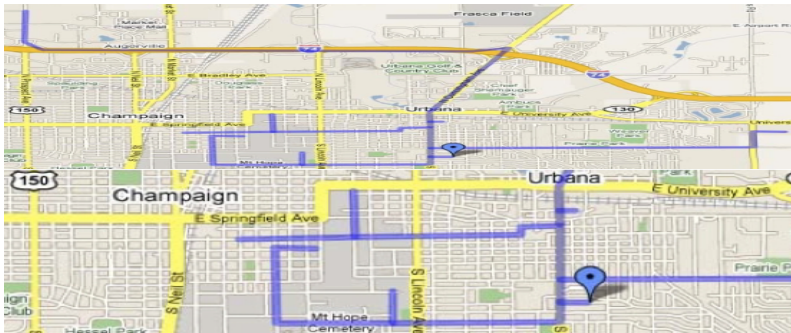
- Graph of habitual visited GPS coordinates



User Habitual Paths

# Per-User Mobility Graph

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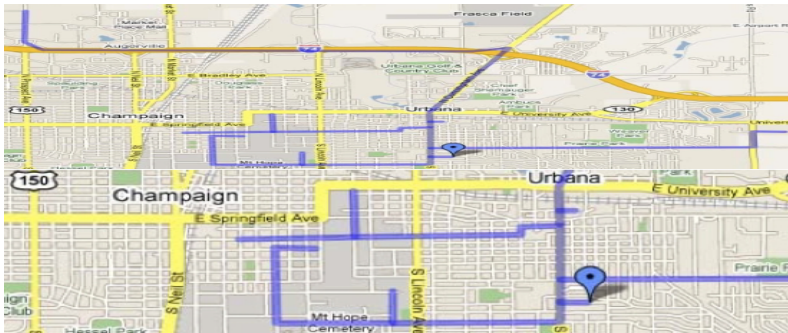
User Habitual Paths

Logical Representation

# Per-User Mobility Graph

## ■ Graph of habitual visited GPS coordinates

- Sample location after branching points
- Predict between branching points
- # of BPs < # of location samples  
(BP = branching point)



User Habitual Paths

Logical Representation

## Evaluation: Habitual Paths

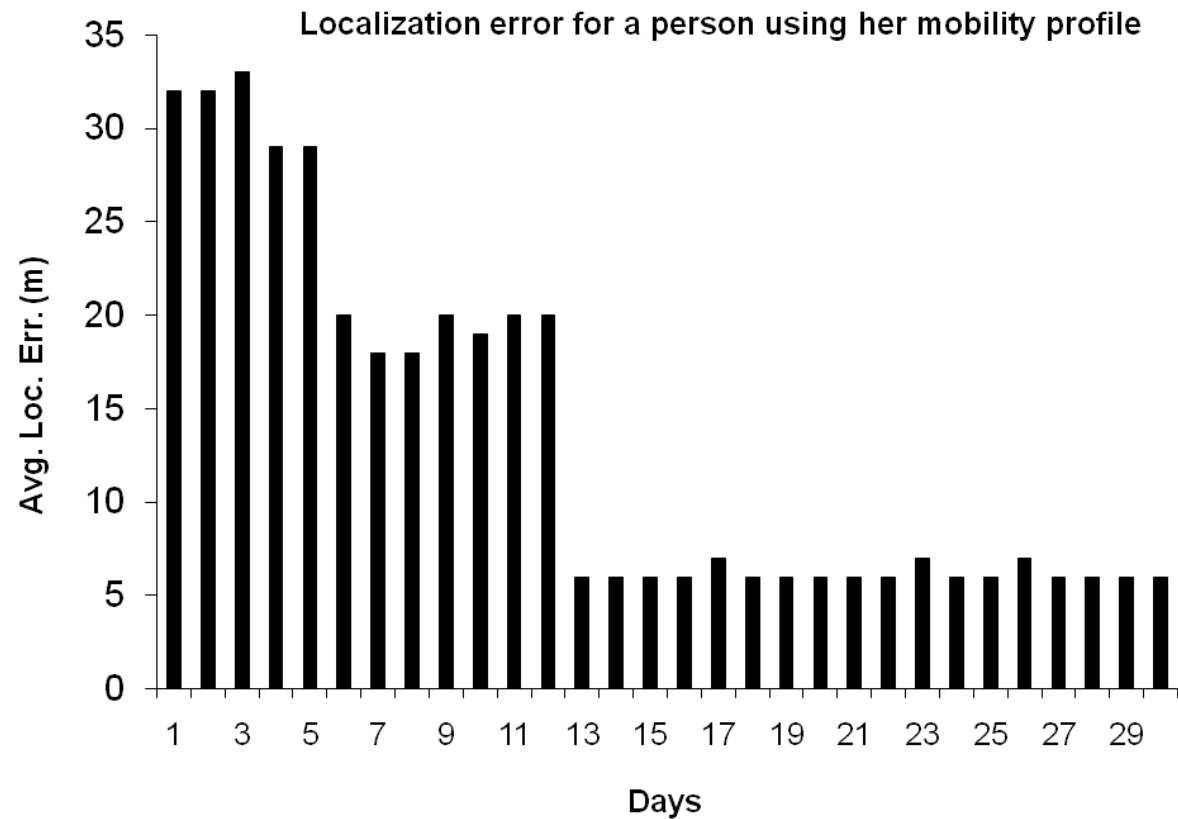
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- 30 days of traces, loc. battery budget 25% per day
- Assume phone speed known

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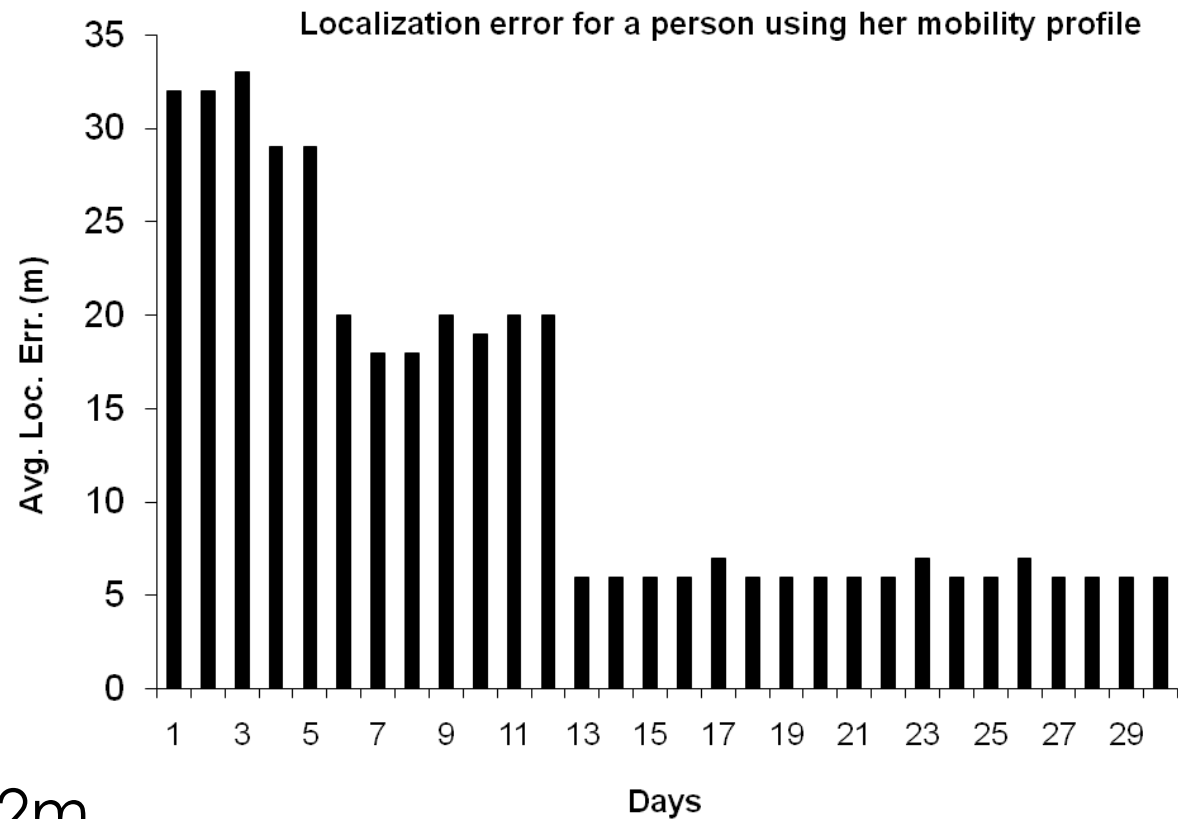
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Average ALE 12m

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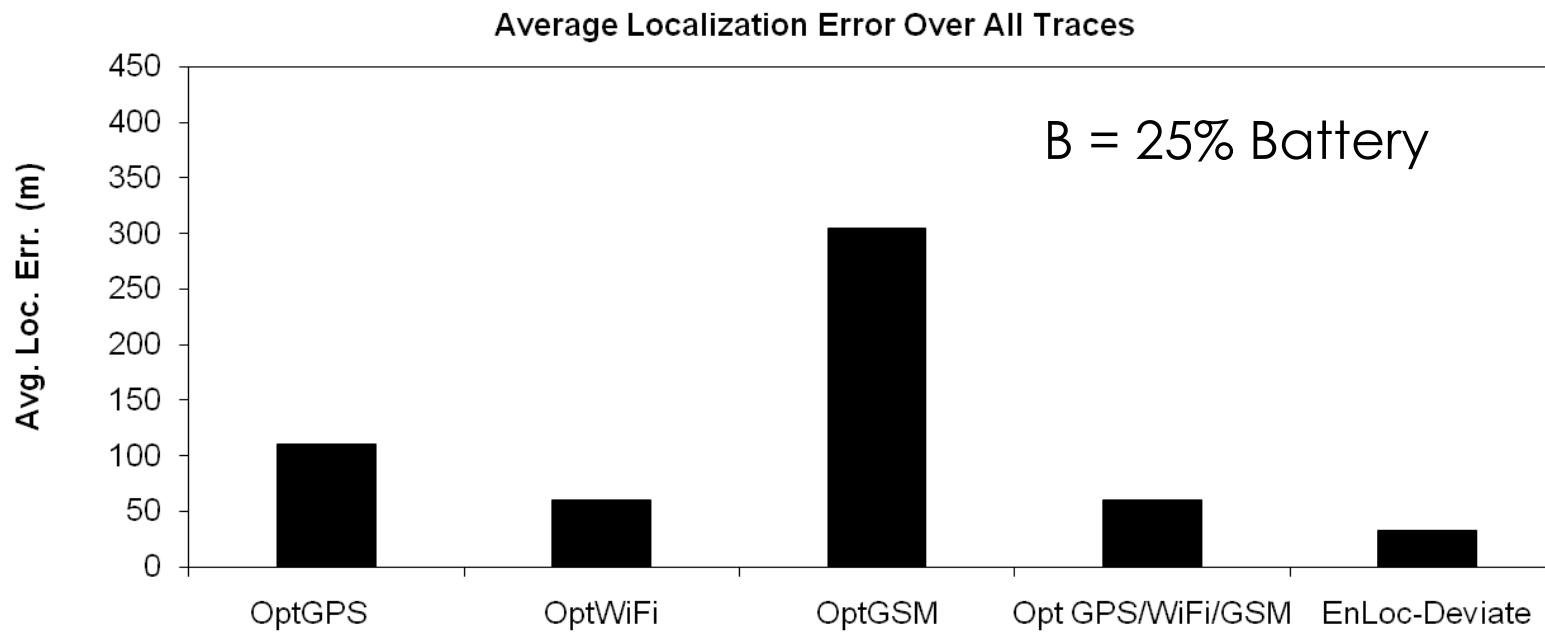
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| Goodwin & Green | U-Turn | Straight | Right | Left  |
|-----------------|--------|----------|-------|-------|
| E on Green      | 0      | 0.881    | 0.039 | 0.078 |
| W on Green      | 0      | 0        | 0.596 | 0.403 |
| N on Goodwin    | 0      | 0.640    | 0.359 | 0     |
| S on Goodwin    | 0      | 0.513    | 0     | 0.486 |

# Evaluation: Population Statistics



OptX: report last sampled location using sensor X (offline)

EnLoc-Deviate: Equally spaced GPS + population statistics (online). ALE ~ 32m

# Future Work/Limitations

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- Assumed phone speed known
  - Infer speed using accelerometer
  - Energy consumption of accelerometer relatively small
  
- Deviations from habitual paths
  - Quickly detect/switch to deviation mode
  
- Probability Map hard to build on wider scale
  - Statistics from transportation departments

# Conclusions

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- Location is not for free
  - Phone battery cannot be invested entirely into localization
- Offline optimal accuracy computed
  - For specified energy budget
  - Known mobility trace
- However, online localization technique necessary
- EnLoc exploit prediction to reduce energy
  - Personal Mobility Profiling
  - Population Statistics

# Questions?

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Thank You!

Visit the SyNRG research group @  
<http://synrg.ee.duke.edu/>

